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ABSTRACT

Latent growth modeling (LGM) has emerged as a flexible analytic technique for modeling change over time because it can describe individual variability in terms of initial status and in growth. LGM methodology can also provide a means for testing the contribution of other variables in order to explain variability in those initial levels and growth trajectories. This paper illustrates the use of LGM as an analytical tool in program evaluation. Specifically, a hypothetical evaluation of a high school drug use prevention program was used to demonstrate: (1) how LGM methodology can be used to assess the longitudinal impact of a prevention program by comparing the treatment to a control group in terms of individual variability in initial status and rate of change; and (2) how predictors of initial status and growth selected on the basis of a particular program theory can be incorporated in the model to explain how the program produced an effect across time. Some advantages and limitations of using LGM in program evaluation are highlighted. (Contains 3 figures and 29 references.) (Author/SLD)

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Using Latent Growth Modeling in Program Evaluation:

A Primer for the Evaluator

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Abstract

Latent growth modeling (LGM) has emerged as a flexible analytic technique for modeling change over time because it can describe individual variability in terms of initial status and in growth. LGM methodology can also provide a means for testing the contribution of other variables in order to explain variability in those initial levels and growth trajectories. This paper illustrates the use of LGM as an analytical tool in program evaluation. Specifically, a hypothetical evaluation of a high school drug use prevention program was used to demonstrate: (1) how LGM methodology can be used to assess the longitudinal impact of a prevention program by comparing the treatment to a control group in terms of individual variability in initial status and in rate of change, and (2) how predictors of initial status and growth selected on the basis of a particular program theory can be incorporated in the model to explain how the program produced an effect across time. Last, some advantages and limitations of using LGM in program evaluation are highlighted.

Using Latent Growth Modeling in Program Evaluation: A Primer for the Evaluator

1. Introduction

In order to overcome some of the limitations of traditional analytic approaches to the assessment of change over time (e.g., repeated measures analysis of variance), a class of methods has recently emerged from the family of structural equation modeling. Such methods are referred to as "Latent Growth Models" (LGM) and approach the analysis of growth from a somewhat different perspective. Specifically, LGM techniques describe individuals' behavior in terms of initial levels and their developmental trajectories from those levels as well as provide a means for testing the contribution of other variables or constructs to explaining those initial levels and growth trajectories (Lawrence & Hancock, 1998; Rogosa & Willett, 1985).

Traditional methods like repeated measures ANOVA focus only on group mean values for each time and thus variability in rate of change at the individual level is not modeled (i.e., this individual variability is captured in the error term). On the other hand, LGM methods simultaneously focus on correlations over time, changes in variance, and shifts in mean values (McArdle, 1986). Thus LGM techniques use more information available in the measured variables than do traditional methods. Recent use of LGM methodology has been to analyze growth in alcohol, cigarette, and marijuana use (see, e.g., Andrew & Duncan, 1998; Duncan & Duncan, 1994; Duncan, Duncan, & Hops, 1998).

The purpose of this paper is to provide program evaluators with a brief introduction to LGM methodology and to some of the recent literature pertaining to its use. Proceeding this, a hypothetical evaluation of a high school drug prevention program is used to demonstrate how LGM could be used to assess the longitudinal impact of a program over time by comparing a

treatment to a control group in terms of individual variability in initial levels and in rate of change over time. Next, a demonstration of how LGM can be used when predictor variables selected on the basis of program theory are incorporated in the model to explain variation in patterns of growth. Last, advantages and limitations of using LGM methodology in program evaluation are highlighted.

2. Latent growth models

Growth curves are a set of statistical models for the study of interindividual differences in change (Willet & Sayer, 1994). This modeling strategy assumes that each individual has his or her own unmeasured (latent) trajectory of growth, which is measured with some inaccuracy. In LGM terminology, "growth" can reflect either a positive or a negative rate of change over time. Because each individual has his or her own growth trajectory, time is nested within the individual. This is referred to as the *within individual* level or the Level 1 model (Kaplan & George, 1998). The basic equation for this within individual level is

$$y_{ij} = ß_{0j} + ß_{1j} t_j + e_{ij}$$

where y_{ij} is the outcome of interest at time i for person j; $ß_{0j}$ represents the initial status at time $t = 0$; $ß_{1j}$ represents the rate of change over time; and e_{ij} is the disturbance (error) term. As one can see in figure 1, latent growth models acknowledge that individuals may grow at different rates.

Insert Figure 1 here

Another assumption is that there is systematic variability in parameters of growth across individuals. Thus the level 1 model can be extended to handle predictors of individual

differences in the initial status and slope parameters. In terms of multilevel analyses, this refers to a *between individual* level or level 2 model. In this case, two models are specified, one for the initial status parameter and one for the slope parameter (Kaplan & George, 1998). The basic equation for this level 2 model can be expressed as

$$ß_{0j} = \alpha_{00} + \gamma_{01} G_j + \zeta_{0j}$$

and

$$ß_{1j} = \alpha_{10} + \gamma_{11} G_j + \zeta_{1j}$$

where α_{00} and α_{10} are intercept parameters representing initial status and rate of change when G_j is zero; γ_{01} and γ_{11} are slopes relating G_j to initial status and rate of change respectfully; and ζ_{0j} and ζ_{1j} are the disturbance terms (Kaplan & George, 1998).

Finally, this model can be further extended to allow individuals to be nested in groups such as in treatment and control groups. In this case, the two groups become the level 3 model. Hence, this model can be used to study intervention (program) effects on initial status and rate of change over time (Kaplan & George, 1998). For a more detailed discussion of how covariance structure analysis (general LISREL model) is used to model individual change over time in accordance with the 3 levels delineated above, see Willett and Sayer (1994).

One major underlying assumption when using the LGM approach to modeling change is that LGM methods assume that individual growth within a particular group follow the same functional form. This does not mean that growth must necessarily follow a linear tend; growth may actually be of a different functional nature (e.g., quadratic or logarithmic). Each individual's growth over this span of time is represented by a line; as such, it may be summarized by a unique *intercept* and *slope*. An individual's intercept describes the amount of the variable possessed at the initial measurement point. The slope captures information about

how much the individual changes for each time interval after the initial measurement point (Lawrence & Hancock, 1998). As a result of individual differences in these intercepts and slopes, changes occur in the relationships among individuals' data across the different time intervals - specifically, an individual's position relative to each other shift across time.

Insert Figure 2 here

In LGM, the intercept and slope are treated as latent variables and are not measured directly. Figure 2 represents an example structural model for linear growth trajectory. Note that in this linear model all paths from the intercept factor are fixed to 1 and all paths from the slope factor to each time point are fixed to 0, 1, 2, and 3. This indicates that the researcher wishes to test whether a model representing linear growth fits the data satisfactory. This also leaves only variance parameters and residuals to be estimated.

To estimate the model in figure 2, the correlation matrix and the means and standard deviations of the measured variables are used as input data. Next, introducing the constant "C" between the intercept and slope factors allows one to estimate the means for both factors. That is, a_1 is the average initial level for the sample (i.e., average score on the outcome variable pre-intervention) and a_2 is the average slope or average rate of change post-intervention. It should be pointed out that the constant "C" is not a variable; it assumes a constant value of one for all individuals and thus has no variance and cannot covary or have an effect on any measured variable or factor. Subsequently, the variance of the intercept and slope factors can be estimated and are denoted as b_1 and b_2 respectfully in figure 2. In addition, the curved double-headed arrow path between the slope and intercept factors denoted as b_3 can also be estimated and

represents the belief that how much one's behavior changes may be related to where one starts out. In other words, a positive value for the estimate b_3 would indicate that on average, those who started out higher at the initial level grow at a positive rate across time. Last, errors on measurement (residuals) are estimated for each time point and are denoted as E1 – E4 in figure 2.

Another unique and powerful advantage of using latent growth modeling methodology is its ability to incorporate predictors of intercept and slope (Lawrence & Hancock, 1998). As will be shown, this may prove useful when a particular theory is used to explain how a program (such as a drug prevention program) effects change. Additionally, LGM methods can be applied to circumstances in which individuals are not measured at the same time intervals. If the number of time points or the spacing between time points vary across individuals, other growth curve techniques are available (e.g., Bryk & Raudenbush, 1987). However, specific constraints need to be placed on the methods for parameter identification. Last, the LGM approach is presented in more technical detail in McArdle (1986), McArdle and Epstein (1987), Meredith and Tisak (1990), Muthén (1991), and Stoolmiller (1994). Applications of the LGM methodology can be found in Duncan and Duncan (1995), and Duncan, Duncan, and Stoolmiller (1994).

3. Implications for program evaluation

When using the LGM approach to the assessment of change over time, any general form of longitudinal data can be studied, including mediational variables influencing the developmental process, ultimate (distal) outcome variables influenced by the developmental process, multiple developmental processes for more than one outcome variable, and treatment-control multiple population studies (Muthén & Curran, 1997). Hence, because this latent

variable framework can be applied to treatment-control multiple population studies, there are implications for its use in program evaluation.

Typical evaluation questions that LGM methodology could address include, "Given individual differences in initial status and in growth, what are the longitudinal effects of a program?" For example, "Is there a slower rate of marijuana use for those exposed to a drug prevention program as compared to students who did not receive the program?" Another question LGM methods might address for the evaluator is, "Do rates at which children learn differ by attributes of the program in which they were exposed?" Questions like these can be answered when continuous data are available longitudinally on may individuals (Willet & Sayer, 1994).

LGM methods have an advantage over the traditional pretest-posttest designs in utilizing more than two waves of data maximize information on individual change. When development follows an interesting trajectory over time, "snapshots" of status taken before and after only are unlikely to reveal the intricacies of individual change (Willet & Sayer, 1994). Hence, LGM methodology can capture long term impact of a program while at the same time capitalizing on individual differences in patterns of change.

Interestingly, assessing program impact via latent variable modeling in general may in fact become more recognized given the flexibility that LGM techniques afford. As Muthén and Curran (1997) point out, "the full potential of the more general longitudinal modeling that can be carried out within the latent variable framework has not yet been realized in terms of real-data analyses of substantive research questions (p. 372)." Thus one challenging area in which such modeling could be examined is within quasi-experimental designs. These types of designs are most often encountered evaluating prevention programs in mental health or education programs.

4. Assessing the longitudinal impact of a program: A hypothetical example

To provide an example, say an evaluator is interested in assessing the impact of an innovative high school drug prevention program across the four years of high school (ninth through twelfth grades). One sample of ninth grade students from an urban school is identified to receive the program at the beginning of the year while a similar sample from another school very similar in characteristics is chosen as a control group.[1] The outcome variable will be frequency and amount of drug use (based on a composite of cigarettes, alcohol, and other drugs) and will be measured at the end of the ninth grade (initial time point), followed by measures taken at the end of tenth, eleventh, and twelfth grades to gauge rate of change across the high school years.

In addition, program theory is considered. The theory underlying the hypothetical program has two components: a psychological and a social component. The psychological component centers on knowledge and perceptions of the health consequences of drug use. The social component centers on social skills like assertiveness, competency, and resistance towards influential drug-using peers. Thus the hypothetical program is designed to prevent students from using drugs over time by providing students with adequate knowledge and perceptions about the consequences of drug use; and at the same time, provide students with good social skills so they can be interpersonally strong during their high school years.

In terms of design and analysis, to explain how this innovative prevention program is

[1] For sake of demonstration, it will be assumed that the two groups are equated at the onset on all measures. However, it is recognized that since random assignment is often unfeasible in this type of evaluation design, other strategies should be used to equate the two groups. In such quasi-experimental designs, time variant and / or time invariant covariates such as pretest measures may be included in the model to adequately equate and compare the two groups.

designed to effect change over time, the two theoretical components must be operationally defined, adequately measured, and included as predictor variables of both initial status and rate of change. For sake of illustration, amount of knowledge / perceptions about drug use are measured using a valid instrument and will be assumed to be measured without error. Similarly, level of social skill is measured by degree of assertiveness and competency, also measured without error. Both of these variables will be measured at the completion of the prevention program. In sum, for those exposed to the prevention program, there will be an increase in amount of knowledge and perceptions, and similarly, an increase in level of social skills due to the program. In turn, this will lead to lower initial levels compared to a control group (following the program year) and slower rate of change (i.e., less drug use over time compared to control) over the high school years.

4.1 Determining program impact based on program theory : Evaluating the growth model

To begin to model change in a way that allows the evaluator to interpret the program effect, a step-by-step analysis strategy is recommended (Muthén & Curran, 1997). The first step is to fit the model to the control group. The control group population represents the normative set of individual growth trajectories that would have been observed also in the treatment group had they not been chosen for treatment. In this single group analysis, it is important to rule out that that the control population exhibits any of the post-intervention changes in growth trajectories that are hypothesized to be due to treatment (Muthén & Curran, 1997). Thus for the control group, the model should statistically fit the data (based on χ^2). As a second step, the treatment model is then analyzed separately and the basic growth trajectory form is investigated.

Keep in mind that for the present theory-driven evaluation of the drug prevention program, the following parameters are of interest and will be assessed: (1) two parameters reflecting the mean of the intercept factor (mean initial level) and mean of the slope factor (average rate of change), (2) two parameters reflecting mean values for each of the two predictors, (3) all 4 path estimates between the two predictors and the slope and intercept factors, and (4) two parameters reflecting the variance of the intercept and slope factors.

Following the single-group analyses, treatment effect can be assessed by conducting a multiple-group analysis (Muthén & Curran, 1997). This requires constraining the 4 alpha parameters, the 4 beta parameters, and the 2 psi parameters to be invariant in the control group and obtaining the χ^2 for this model. Following this, each of the ten parameters are freed in the treatment model one at a time. A significant change in χ^2 from this treatment model compared to that of the control model of the previous step will reveal if that parameter is significantly different from that of the control group. Thus, the effect of treatment is assessed by comparing the set of means and trajectories in the treatment population with those in the control population.[2]

To provide an example, consider figure 3 which shows the complete model (used for both the control and treatment groups).

Insert Figure 3 here

[2] The analysis of evaluation data can be easily carried out using LISREL due to its flexibility and convenience for estimating specific parameters in the model (Jöreskog & Sörbom, 1993). In LISREL procedure, the paths from each intercept and slope factors to each observed time point are fixed in the λ_x matrix according to figure 1 and 2 (assuming a linear trajectory). The intercept and slope variances are free to be estimated in the ψ matrix; errors or residuals are also free to be estimated in the θ_ε matrix; and slope and intercept means are free to be estimated in the α matrix. Last, in the case like in figure 3 where predictors are incorporated, path coefficients are estimated in the beta matrix.

The 10 parameters to be assessed are labeled 1 through 10 on the diagram. Parameter 1 refers to alpha 1 or the mean drug use at the end of ninth grade (i.e., initial status). When this parameter is freed for the treatment model in the multi-group analysis and change in χ^2 value is determined to be significantly different from that of the control group when all parameters were constrained to be invariant, this indicates that, for the treatment group, the mean drug use at the end of ninth grade is significantly different than that of the control (This of course assumes that the two groups are equated at the very beginning). In this example, if the mean value is lower than that which was estimated for control group, this will show that the prevention program had an effect at the initial level.

Parameter 2 in figure 3 reflects the average rate of change over the high school years. As with parameter 1, if this parameter is significantly smaller based on χ^2 difference test, this will indicate a slower rate of drug use for the treatment group compared to the control group. Parameter 3 and 4 in figure 3 refers to alpha 3 and 4 respectfully, and these represent the mean level of knowledge / perceptions and mean level of social skill. If the two groups are equated at the beginning, then a significant difference in means (where the means for the treatment group are larger then the control) for these two predictors will indicate that the prevention program significantly increased amount of knowledge / perceptions and social skill for those exposed to the program (of course again assuming the groups were equated at the beginning and selection bias is not a threat; if not, a pretest covariate for each predictor might be used).

To determine if the two predictors account for a significant amount of variability in initial levels and rate of change as suggested by program theory, the 4 beta parameters or path coefficients labeled 5, 6, 7, and 8 in figure 3 are tested. Based on the present hypothetical evaluation, it is hypothesized that for those in the prevention program, the program will lead to

higher amounts of knowledge and correct perceptions and greater levels of social skill. This in turn, will lead to lower initial levels and slower rate of change over time for the treatment group. To test this, each of the 4 path estimates for the treatment group is compared to those in the control group one at a time in the multi-group analysis. If change in χ^2 is significant for each test and the paths are in the right direction and statistically significant (in this example, all 4 paths should be negative and significantly larger than those for control group), then one can conclude that the predictors may explain initial levels and rate of change for those in the treatment group. Thus the prevention program appears to have a longitudinal impact and operates according to the program theory. Last, parameters 9 and 10 in figure 3 represent the variance of the intercept and slope factors and can be assessed for the treatment group and compared to that of the control group.

5. Why include predictors on the basis of program theory to assess the longitudinal impact of a program?

In many instances, evaluators incorporate program theory in their evaluation design in order to assist them in understanding how the program produced (or failed to produce) its intended and perhaps unintended effects (Chen, 1990, p. 171). Specifically, causal mechanisms of a program should be examined within the framework of the program's theory and so the traditional input-output assessment leads an evaluator to provide impoverished version of causal inference (Cordray, 1986; Trochim, 1986b). Thus, allowing theory to drive the evaluation broadens the evidential basis by actively considering plausible rival explanations, by examining implementation procedures, and by investigation mediation and contextual factors.

The shift in program evaluation from method-oriented evaluations ("black box") to theory-oriented evaluations has sparked debate among many evaluators (e.g., Chen, 1990; Bickman, 1987; Weiss, 1997). Although the idea of incorporating theory in evaluation design has generated considerable interest, some problems beset its use (see Weiss, 1997 for a discussion of the limitation to using theory to drive the evaluation process). Nevertheless, most evaluators find it important to integrate, at least in part, program theory into the evaluation process.

Bickman (1987) provides a list of benefits that can result of articulation of program theory and its integration with program evaluation. Advantages include: (1) specifying the underlying theory of a program within the evaluation allows that theory to be tested in a way that reveals whether program failure results from implementation failure or theory failure; (2) program theory clarifies the connections between a program's operations and its effects, and thus helps the evaluator to find either positive or negative effects that otherwise might not be anticipated; (3) program theory can also be used to specify intermediate effects of a program that might become evident and measurable before final outcomes can be manifested, which can provide opportunities from early program assessment in time for corrective action by program implementers; and (4) program theory may be the best method of informing and educating stakeholders so that they can understand the limits of the program.

Needless to say, program theory can also be incorporated within a LGM approach to assess whether or not a program has a longitudinal impact over time (i.e., a preventive effect). In the simplest terms, this can be done by testing the contribution of predictor variables (based on program theory) in order to explain interindividual variability in initial levels and in rate of change over time. Including such variables allow the evaluator to pinpoint those factors in the

causal chain that lead to program success or failure. This kind of diagnostic function can provide useful information for future program improvements (Chen, 1990, p. 191). Moreover, testing theoretical predictors of initial status and growth can be carried out under the framework of structural equation modeling, thus makes it possible to implement LGM methodology when longitudinal effects of a program are of interest to stakeholders and evaluators.

6. Advantages and limitations of using LGM in program evaluation

As seen in the previous examples, the major advantage of utilizing a structural equation modeling approach to modeling change is its flexibility in that it can capitalize on variability in individual differences in initial status and in growth over time. Subsequently LGM is easy to implement using existing software programs like LISREL (Kaplan & George, 1998). The various goodness-of-fit indices provided by LISREL allow for a wide variety of substantively interesting hypotheses to be tested, such as test the adequacy of the hypothesized growth form. The structural equation modeling approach also allow for the study of more than one outcome (see Willet & Sayer, 1996). In addition, Kaplan and George (1998) point out that utilizing a structural equation modeling approach to model latent growth allows one to incorporate multiple indicators of the outcome of interest at each time point, thus accounting for the problems of measurement error (in the previous example, only observed variables were used for sake of simplicity). In addition, using structural equation methodology allows one to easily handle missing data (see Muthén, 1993) as well as allow one to incorporate categorical variables (see Muthén, 1996).

Specifically, when program theory is used, applying LGM methodology is beneficial mainly because it allows the evaluator to test the contribution of predictors of growth (as dictated by theory) and the evaluator can incorporate both fixed and time varying covariates as suggested by program theory. In the example above, the evaluator may want to adjust for other psychological variables or demographics like gender, SES, or ethnicity (depending on the program) that may be hypothesized, according to program theory, to explain drug use. Using LGM within the evaluation of a drug prevention program over time allows growth on several constructs (e.g., drug and alcohol use) simultaneously. This of course depends on the program theory and how it is utilized.

Other postulated benefits afforded from a theory-driven standpoint echo some of the benefits proposed by Bickman (1987). Keeping with the above example, one benefit may be that specifying the underlying theory of the development of drug use within the evaluation allows that theory to be tested in a way that reveals whether program failure results from implementation failure or theory failure. In addition, program theory clarifies the connection between the program's operation (knowledge and social skills) and its effect on drug use over time. Furthermore, using a traditional approach such as repeated measures ANOVA designs or conventional pretest-posttest designs do not take advantage of individual differences or variability in change over time. Perhaps in utilizing a LGM approach with a theory-driven evaluation design may prove to be the best method of informing and educating stakeholders so that they can understand the limits of the program

One of the most obvious disadvantages in using LGM methods in assessing program impact is the fact that it requires measures of an outcome at multiple time points. Attrition may be a problem leading to missing data. Fortunately, Muthén, Kaplan, and Hollis (1987) and

Muthén (1993) discuss how to handle missing data in the latent variable framework in general, and Duncan & Duncan (1994) and Schafer (1997) discuss how to model incomplete data due to attrition in the LGM framework in particular.

Because LGM uses structural equation modeling (SEM) methodology, it shares many of the same weaknesses. LGM methods assume multinormally distributed variables, and assume that change is systematically related to the passage of time, at least over the time interval of interest. Subsequently, the application of LGM within the SEM framework depends, at least ideally, on data that are collected when individuals are observed at approximately the same time, and on the number and spacing of assessments are the same for all individuals (longitudinal panel data are typical of this design).

Apart from LGM's novelty and that it requires at least some working knowledge of structural equation modeling, one possible resistance stymieing an accelerated application of LGM in program evaluation, particularly within a theory-driven context, might be due to the issue of evaluation design. Many evaluations are restricted to using a nonequivalent groups pretest-posttest design - - mainly due to cost and convenience (time). In a theory-driven context, more measures are needed to capture the distal and mediating variables that are modeled and so, depending on the program (planner and stakeholder interest), might be superfluous. In addition, LGM require at least three time intervals, and so limit the use of LGM directly when only one posttest measure is taken. This places more emphasis on the use of LGM in evaluation prevention type programs. Finally, when incorporating LGM as an analytic tool in non-randomized designs, selection bias still pose as a threat as in the non-equivalent group comparative change design (however using covariates such as pretest measures in the model to equate the groups can be incorporated). It seems this issue will always rear its ugly head!

7. Conclusion

Latent growth models are obviously not the only way to model change (repeated measures ANOVA models remain valid given statistical assumptions and the evaluator's goal). However, LGM is a more versatile tool. Program evaluators who wish to determine inter-individual rates of change and predictors of that change may want to incorporate latent curve analyses into their repertoire. Because program theory often drives many evaluations (as argued by Chen, 1990), evaluators may find LGM a useful and powerful analysis when the goal is to assess the longitudinal impact of a prevention program is used and when individual variability at initial levels and individual rate of change is a desired feature as a result of some implemented social or educational program.

This paper may serve as an primer for future examination of the potential utility of LGM methodology within the program evaluation context. Subsequently, this paper proffers a prototypical model for evaluators interested in determining longitudinal change as a result of some program implemented over time, specifically evaluators who conduct theory-driven evaluations. In short, because the focus of this paper was conceptually rudimentary and centered mainly on one hypothetical scenario, future research should focus on some of the methodological and statistical issues inherent with this approach.

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Figure Legend

Figure 1. Individual growth curves across five timepoints.

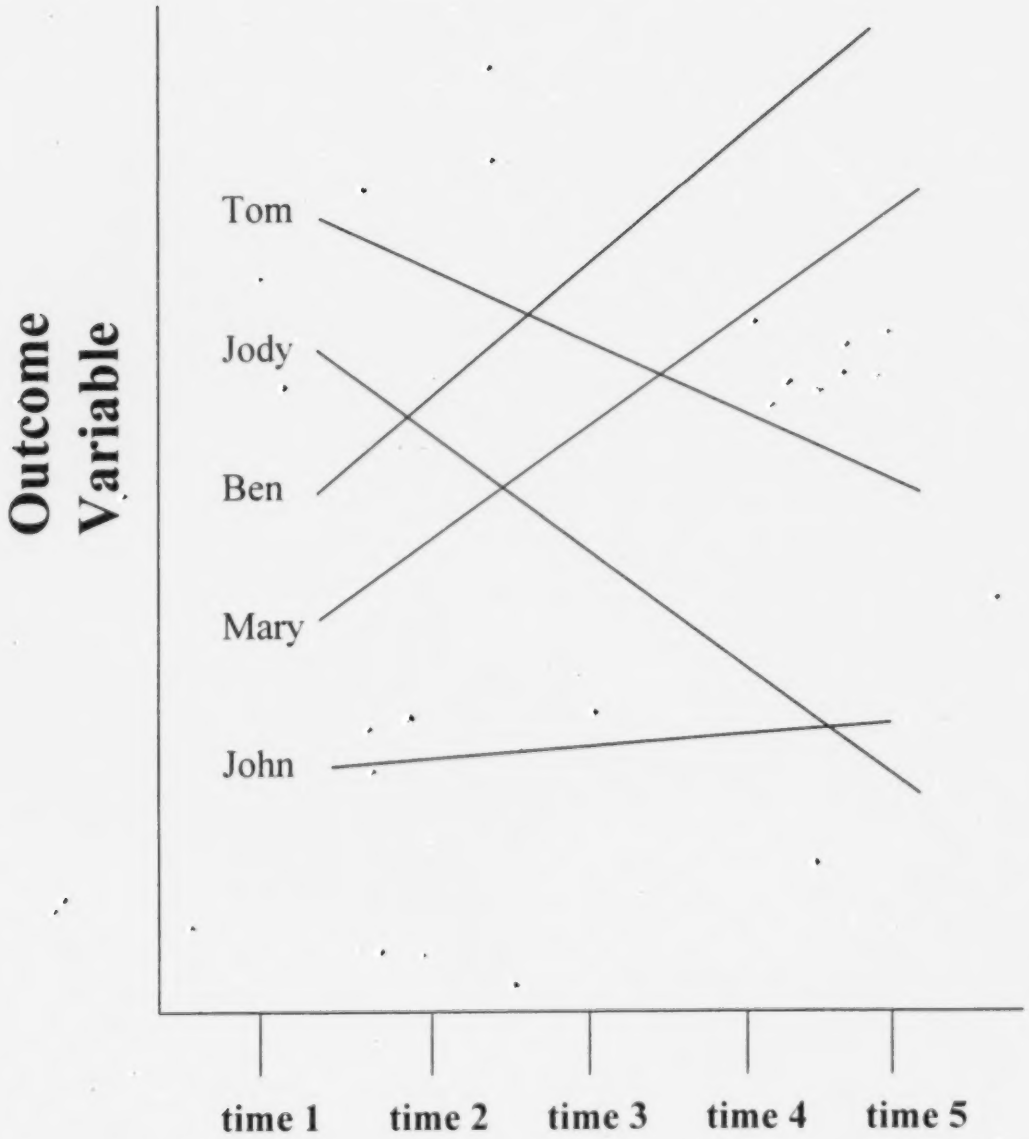

Outcome Variable
Tom
Jody
Ben
Mary
John
time 1
time 2
time 3
time 4
time 5

Figure legend

Figure 2. A structural model for linear growth trajectory.

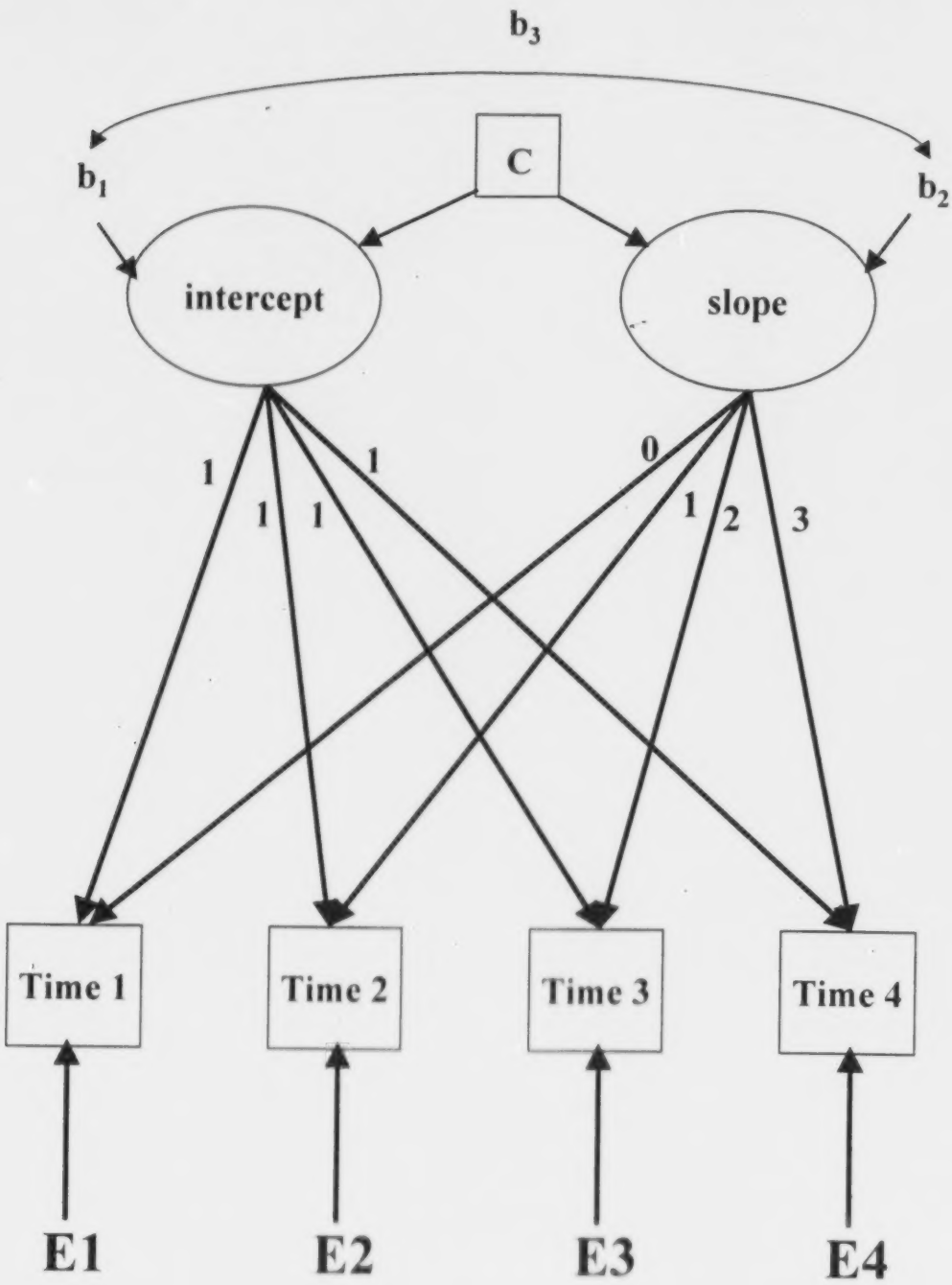
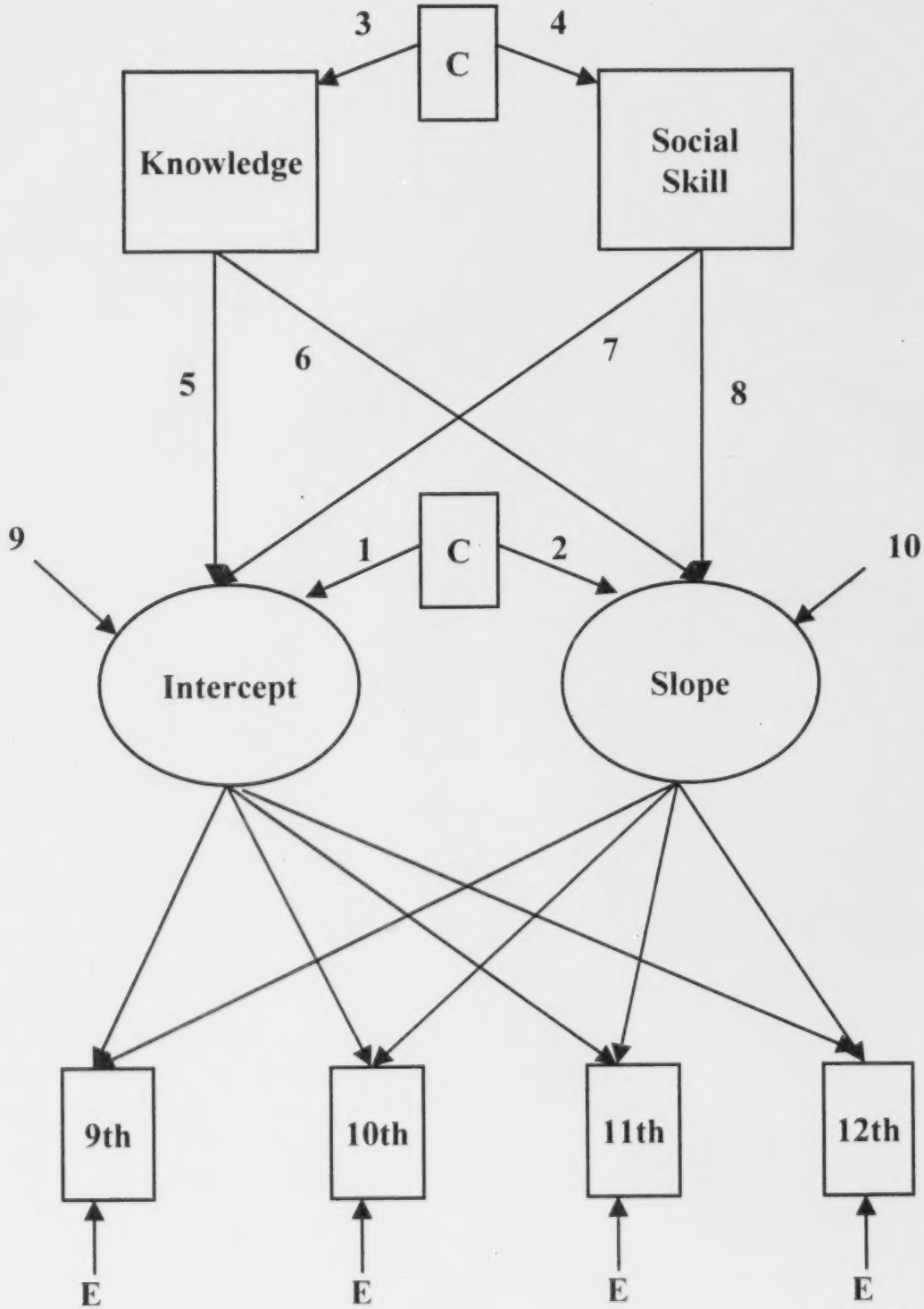

b3
b1
C
b2
intercept
slope
1
1
1
1
0
1
2
3
Time 1
Time 2
Time 3
Time 4
E1
E2
E3
E4

Figure Legend

Figure 3. A growth model for an intervention study comparing a treatment and a control group based on program theory.


3
C
4
Knowledge
Social
Skill
5
6
7
8
9
1
C
2
10
Intercept
Slope
9th
10th
11th
12th
E
E
E
E